Intelligent Neural Network Implementation for SOCI Development of Li/CFx Batteries

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***Abstract*— The State Of Charge Indicator (SOCI) for the Lithium Poly Carbon Monoflouride (*Li/CFx*) battery has a wide range of applications. However, the dynamic environmental conditions, such as the ambient temperature, can alter the characteristic response of the battery and introduce non-linear behavior. This paper discusses the in-lab development of an Artificial Neural Network (ANN) based SOCI for the *Li/CFx* battery. The ANN is trained on the recorded data – voltage, current and ambient temperature, to produce a non-linear model and to accurately predict the State Of Charge (SOC) of the battery. The SOC prediction is based on the recent behavior of the battery. Preliminary experimental results using recorded datasets from the Battery Design Studio are presented for the Lithium Ion battery. The working model for the *Li/CFx* is currently under development. The reported results demonstrated good performance of the developed SOCI, with less than 2% average relative error on data at previously observed ambient temperatures.**

***Index Terms*— *Li/CFx* Batteries, State of Charge, Artificial Neural Networks**

I. Introduction

THE State Of Charge Indicator (SOCI) is an essential part of many user-friendly electronic device batteries. For instance, electronic watches, cellular telephones, pagers, laptops, calculators or portable medical devices are typically equipped with a SOCI, reporting the current state of the battery [1]. It enables the user to assess the remaining operational time. Clearly, this can be essential in operations, where inaccurate information about the remaining operational time can be critical or fatal. Because the portable devices are required to operate in various environmental conditions, the SOCI should account for additional factors, such as the ambient temperature, which can substantially affect the behavior of the given battery.

A SOCI for the Lithium Polycarbon Monoflouride (*Li/CFx*) battery is considered in this paper. Even though the SOCI for the *Li/CFx* was developed by private industry, currently there is no SOCI solution for the *Li/CFx* battery that would account for the non-linear effects of the environmental conditions. The *Li/CFx* batteries are used for example for medical industry pacemakers, and other portable devices [2].

This paper discusses the "in-progress" development of an intelligent SOCI for the *Li/CFx* battery, by means of Artificial Neural Networks (ANNs). Currently, the research effort is based on recorded data for the widely used Lithium Ion (*Li/Ion*) battery using the Battery Design Studio. The working model for the *Li/CFx* battery is under development. Due to the inherent similarities of both batteries, the current preliminary results will be later used towards the ultimate goal of developing an intelligent SOCI for the *Li/CFx* battery.

Artificial Neural Networks (ANNs) are powerful machine learning paradigm capable of data-driven synthesis of complex non-linear models of the system of interest [3]-[5]. The synthesis proceeds in a supervised manner. Hence, the ANN attempts to minimize the classification error defined as the difference between the desired and the actual response of the model.

In the presented SOCI development, the ANN architecture is trained on input data obtained from various test procedures of the battery. The model predicts the current SOC of the battery based on the recent history of the voltage, current and the ambient temperature. Hence, the model accounts for non-linear behavior introduced by the varying environmental conditions into the system.

The rest of the paper is organized as follows. Section II gives a brief background of the *Li/Ion* and the *Li/CFx* batteries and of the architecture and the training of the ANNs. Section III provides analysis of the data acquisition setup and the recorded data itself. The design of the intelligent SOCI is presented in Section IV. Up-to-date experimental results are reported in Section V. The paper is concluded in section VI.

II. Background

This section gives a brief overview of the *Li/Ion* and the *Li/CFx* batteries as well as of the Artificial Neural Networks.

A. Li/Ion Batteries

Lithium Ion batteries are one of the most common batteries in portable consumer electronics. The battery consists of carbon anode, metal oxide cathode. They are surrounded by lithium salt electrolyte in an organic solvent [6]. The main advantages of Li/Ion batteries are their high energy density, low maintenance, no need for periodic discharge and fast and low self-heating charging [7]. Moreover, they do not suffer from the common memory effect and can be purchased at accessible costs.

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B. Li/CFx Batteries

The compound of the *Li/CFx* battery is synthesized by a direct fluorination of carbon with fluorine gas at temperatures of 300^0C to over 600^0C. The positive electrode is a composition of lithium poly-carbon monoflouride, acetylene black conductor and poly-tetrafluorethulene binder. The negative electrode is manufactured by press-filtering the lithium metal onto the current collector. Organic electrolyte is used. Gamma-butyrolactone is used for the cylindrical cell and a mixture of propylene carbonate and 1,2-dimethoxyergane for the coin cell [8]

The main advantages of *Li/CFx* batteries are their higher energy density, longer shelf life and improved low and high temperature operation [9].

C. Artificial Neural Network

Artificial Neural Networks (ANNs) constitute powerful computational paradigm, capable of non-linear modeling of the system of interest [3]-[5]. Since their origin, they were applied in wide range of engineering applications such as, pattern recognition [10], signal prediction [11] or intrusion detection [12].

Originally inspired by the biological neural system, ANNs are typically composed of multiple simple processing units – neurons, organized in multiple layers. Each neuron first acts as a summation unit computing the sum of the incoming m-dimensional input signals – $X(t)=\{x_1(t),\ldots, x_m(t)\}$, weighted by the synaptic weights - w_i. Further, the obtained net value is transformed through the activation function - φ, to produce the final output – $y(t)$:

$$y(t) = \varphi\left(\sum_{i=1}^{m} x_i(t)\, w_i\right) \tag{1}$$

Fig. 1 depicts the artificial neuron model.

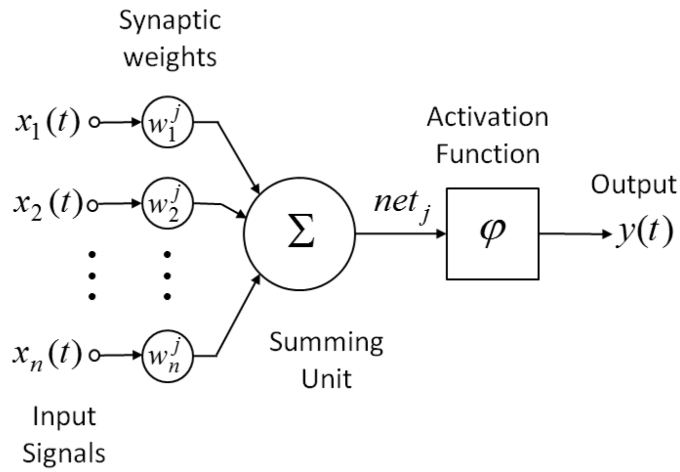


Fig. 1. Artificial neuron model.

The feed-forward ANN considered here is trained in a supervised manner. Hence, the desired response $d(t)$ has to be provided for each input pattern $X(t)$. The presented ANN-based SOCI uses a hybrid training algorithm, combining the Levenberg-Marquardt (LM) method with the Error Back-Propagation (EPB) learning rule [4], [13], [14]. This method was developed with the intention to overcome some of the limitations of the standard EPB algorithm, utilizing the classical numerical optimization techniques.

The goal of the training process is to iteratively minimize the total classification error given by:

$$E = \sum_{i=1}^{N}\sum_{p=1}^{P}\left(d_p(t) - y_p(t)\right)^2 \tag{2}$$

Here, N and P stand for the number on input patterns and the number of output neurons, respectively. (2) can be further simplified into:

TABLE I
BATTERY DESIGN TEST PROCEDURE AT 20C

Step		Control Condition		End Condition		Limit Condition		Report		
#	Type	Type	Value	Type	Value	Type	Value	Volts [V]	Time	Temp [^{0}C]
1	Discharge	Current	0.42 A	Time	3.4583 hr	Voltage	4.167 V	0.01	10 min	20
2	Rest			Time	10 min			0.01	10 min	20
3	Discharge	Current	0.42 A	Voltage	2.8 V			0.01	10 min	20
4	Rest			Time	20 min			0.01	5 min	20
5	Charge	Current	1.68 A	Time	2.5 hr	Voltage	4.167 V	0.01	2.5 hr	20
6	Rest			Time	10 min			0.01	10 min	20
7	Discharge	Current	1.05 A	Voltage	2.8 V			0.01	10 mn	20
8	Rest			Time	20 min			0.01	5 min	20
9	Charge	Current	1.68 A	Time	2.5 hr	Voltage	4.167 V	0.01	2.5 hr	20
10	Rest			Time	10 min			0.01	10 min	20
11	Discharge	Current	2.10 A	Voltage	2.8 V			0.01	10 min	20
12	Rest			Time	20 min			0.01	5 min	20
13	Charge	Current	1.68A	Time	2.5 hr	Voltage	4.167 V	0.01	2.5 hr	20
14	Rest			Time	0			0.01	10 min	20
15	Discharge	Current	4.20 A	Voltage	2.8 V			0.01	10 min	20
16	End									

$$E = \sum_{i=1}^{N} \sum_{p=1}^{P} \left(e_p(t)\right)^2 \qquad (3)$$

The LM method derives its weight update rule from the original Newton's method:

$$\Delta W = A^{-1} g \qquad (4)$$

Here, A and G constitute the Hessian and the gradient, respectively. Considering the error E in (3), which is a sum of squares, the Hessian and the gradient can be computed as:

$$A = 2J^T J \qquad (5)$$

$$g = 2J^T \vec{e} \qquad (6)$$

Here, $\vec{e}$ denotes the vector of the error signal and J is the Jacobian of the partial derivative of the error with respect to the weight set. In the used hybrid training algorithm, the Jacobian is computed using a modified EBP algorithm.

In order to alleviate the problems with ill-defined Jacobian matrices, the LM method introduces an identity matrix I and a learning parameter μ. Hence, the LM weight update rule can be formalized as:

$$\Delta W = \left[J^T J + \mu I\right]^{-1} J^T \vec{e} \qquad (7)$$

By setting $\mu = 0$, the LM algorithm reduces to the Gauss-Newton method. For larger values of μ the steepest descent technique is implemented. The actual value of parameter μ is dynamically controlled. It is initially set to *0.001*. When the total error (3) increases (decreases), value of μ is multiplied (divided) by 10.

III. Data Acquisition and Analysis

The battery testing procedure using the Battery Design Studio is described in this section. Further the recorded parameters are defined together with the computation of the SOC.

A. Battery Design Studio

Battery Design Studio was used to simulate the *Li/Ion* battery discharge characteristics [15]. Battery Design Studio is computer aided drafting program which performs the SOC simulations based on battery chemistry parameters. Since there is not a current working model for *Li/CFx* at this time, simulations were run for a 2.25Ah *Li/Ion* battery. These simulations included numerous testing patterns with different charge/discharge rates at different ambient temperatures. Table I shows an example of the testing procedure.

The output parameters from Battery Design Studio are Time [Hours], Voltage [Volts], Current [Amps], Temperature [^{0}C], and Cycle Capacity [Ah].

The Battery Design Studio model for the *Li/CFx* is under development. The *Li/Ion* battery was chosen for this initial stage of the research effort for its similarities with the *Li/CFx*. The current preliminary results will be later used towards the ultimate goal of developing an intelligent SOCI for the *Li/CFx* battery.

B. Data Analysis

Multiple parameters are being recorded during the testing procedure. Namely at each time sample the Voltage [Volts], current [Amperes], temperature [^{0}C] and the Cycle Capacity [Ah] are measured. The SOC value can be calculated as the normalized difference between the given battery capacity and the measured cycle capacity:

$$SOC(t) = \frac{BatteryCapacity - CycleCapacity(t)}{BatteryCapacity} \qquad (8)$$

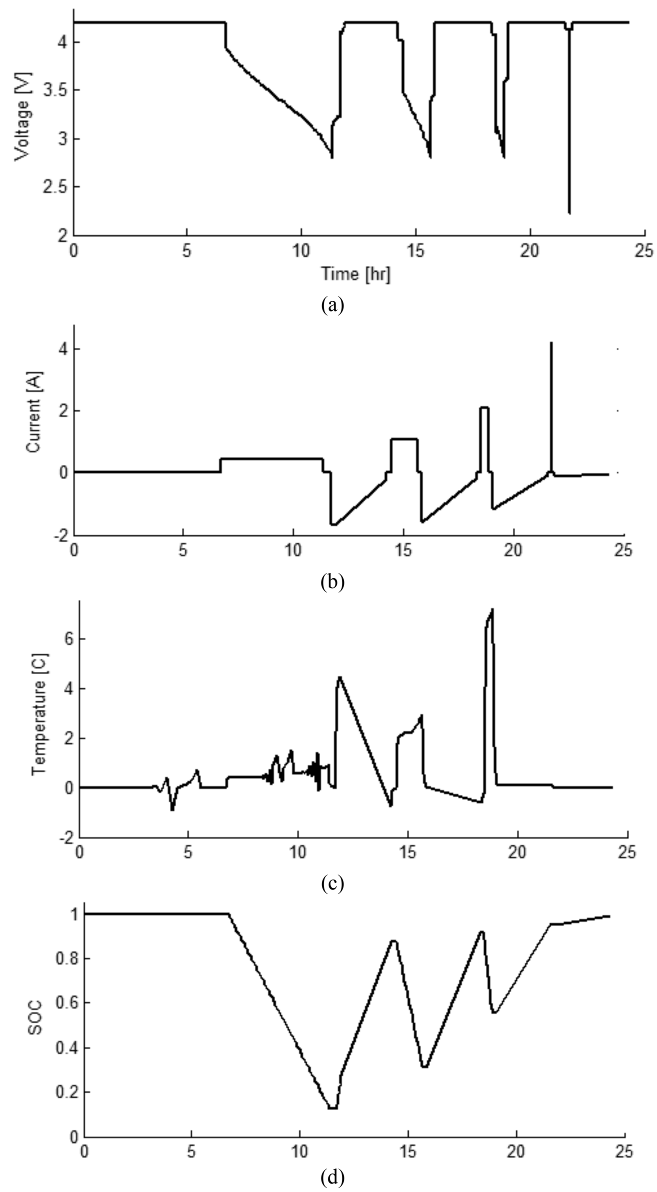


Fig. 2. Recorded voltage (a), current (b), temperature (c) and SOC (d).

By recording the testing procedure at different temperatures, various charging and discharging behaviors were obtained. Thus, it is believed that the temperature has a significant impact on the battery characteristic and thus on the SOC prediction and it has to be considered in the developed model. Fig. 2 shows the recorded voltage, current and temperature along with the computed SOC at 0^0C during the testing sequence.

IV. Intelligent SOC Indicator

This section discusses the development of an ANN-based intelligent SOC indicator system.

A. Data Preprocessing

The developed SOCI outputs the prediction of the actual SOC of the given battery. Since, the ambient temperature is believed to introduce non-linear elements into the dependence of the SOC on the voltage and current, the Artificial Neural Network (ANN) is utilized.

The current value of SOC at time t is being predicted based on the recent history of the battery life. Thus, the task of the ANN is to process the input vector containing the recent measurements and output the SOC prediction at given time. The non-linear model of the battery behavior is constructed by a supervised training process. Empirically, a 7 dimensional input vector was constructed. The recent three measurements of voltage - $vol(t)$ and current - $curr(t)$ combined with the current ambient temperature measurement - $temp(t)$ constitute the input attributes. The output is the current value of SOC – $SOC(t)$. Hence, the training dataset is composed of input vectors $X(t)$ and the desired response $d(t)$:

$$X(t) = \{vol(t), vol(t-1), vol(t-2), curr(t), curr(t-1), curr(t-2), temp(t)\} \tag{9}$$

$$d(t) = \{SOC(t)\} \tag{10}$$

The process of transforming the stream of measured data into the training vectors $X(t)$ is depicted in Fig. 3.

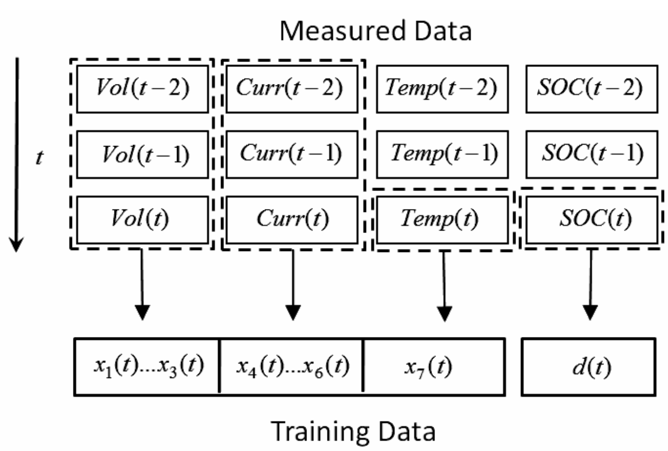


Fig. 3. Extraction of the training data from the measured data.

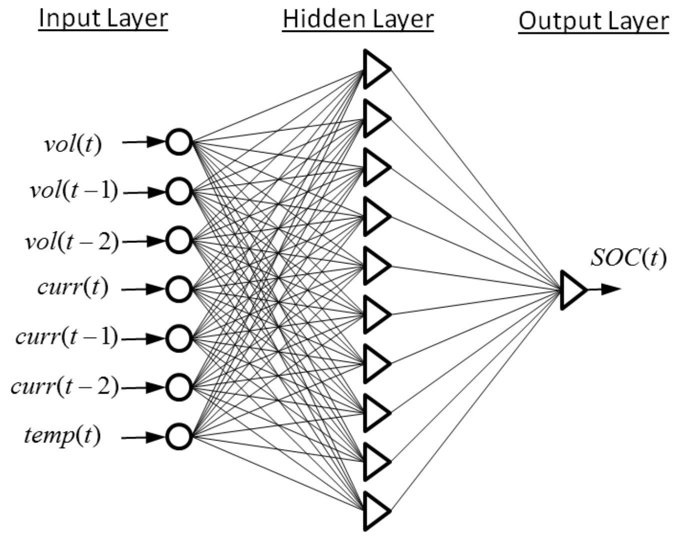


Fig. 4. ANN-based SOC Indicator.

B. ANN Based SOC Indicator

A feed-forward ANN was used to model the non-linear behavior of the SOC characteristic for the *Li/CFx* battery. The neural network was trained in a supervised manner. The training vectors defined in (10) and (11) were used.

A specific combination of two neural network training algorithms – the Levenberg-Marquardt (LM) method and the Error Back-Propagation (EBP) learning algorithm - was used. This training algorithm was selected for its fast convergence and stable performance.

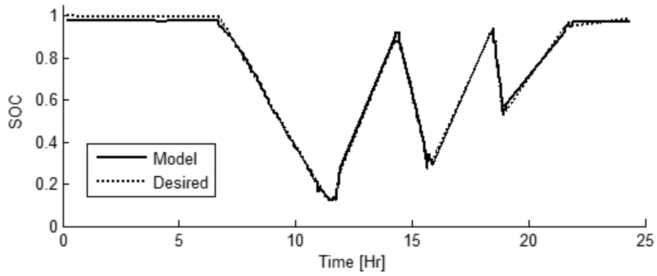
Experiments were done in order to determine the optimal architecture of the designed ANN. It was concluded that ANN architecture with 1 hidden layer is sufficient to accurately model the given problem. The final architecture used 10 neurons with hyperbolic tangent transfer function in the hidden layer and 1 output neuron with sigmoidal transfer function. Fig. 4 displays the chosen ANN architecture.

V. Experimental results

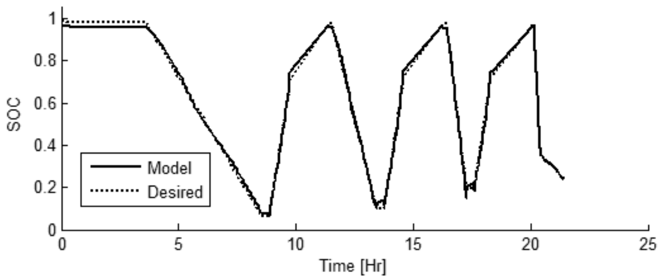
Several experiments were carried out in order to determine the performance and accuracy of the developed ANN-based SOC indicator for the *Li/CFx* batteries. Up to this date, the testing procedure was executed on training data recorded for 3 different ambient temperatures – 0^0C, 40^0C and 75^0C for the *Li/Ion* battery. In future work, more data will be measured, covering the whole theoretical operational temperature range of *Li/CFx* batteries with sufficient density. Therefore, the presented experimental results can be considered preliminary and they will be subject to further improvements.

A. SOC Prediction Complexity

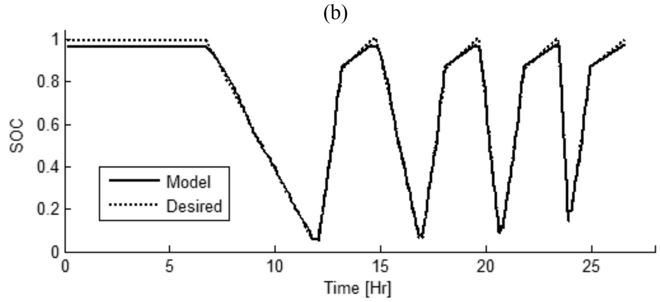
Firstly, the complexity of the problem of SOC prediction as well as the suitability of the designed ANN architecture (Fig. 4) was analyzed. While ultimately the ANN-based model should generalize over previously unseen data, it initially needs to be powerful enough to capture the recorded behavior. Hence, the ANN-based SOCIwas trained on measured data at all three recorded ambient temperatures – 0^0C, 40^0C and 75^0C.



(a)



(b)



(c)

Fig. 5. ANN-based SOC prediction at 0C (a), 45C (b) and 75C (c).

Consequently, the system was tested on particular sequences and the average relative error was measured. Because the *SOC*(*t*) is a value between 0 and 1, the average relative error can be computed as:

$$Err = \frac{1}{N}\sum_{i=1}^{N}\left|SOC(t) - d(t)\right| .[100\%] \qquad (11)$$

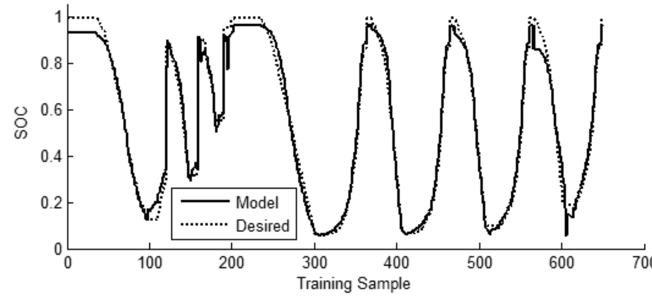
The experimental results are reported in Table II. Further, the prediction and the desired response are visually compared in Fig. 5. The results demonstrate a good performance of the developed model, when the average relative error was fewer than 2%. This suggested that the designed ANN-based SOCI is capable of modeling the non-linear behavior of the SOC parameter for the *Li/Ion* batteries. In future work the same technique will be applied to data from the *Li/CFx* battery.

TABLE II
ANN-BASED SOCI PREDICTION ERROR

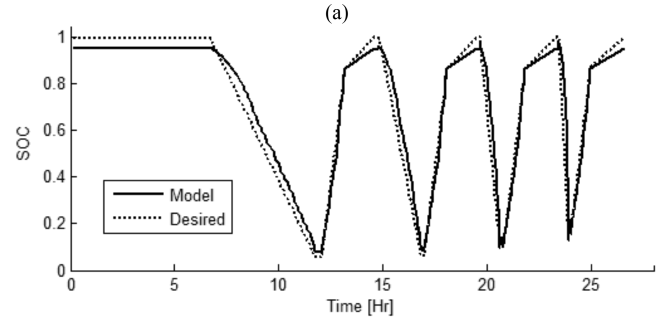
Training Set	Testing Set	Avg_Train_Err
0C, 40C and 75C	0C	1.70%
0C, 40C and 75C	40C	1.42%
0C, 40C and 75C	75C	1.26%

TABLE III
ANN-BASED SOCI PREDICTION ERROR

Training Set	Testing Set	Avg_Train_Err	Avg_Test_Err
0C and 75C	40C	1.37%	8.11%
0C and 40C	75C	1.20%	4.91%
40C and 75C	0C	0.60%	17.61%

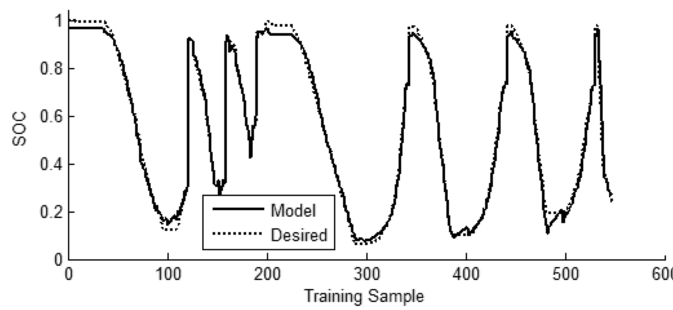


(a)

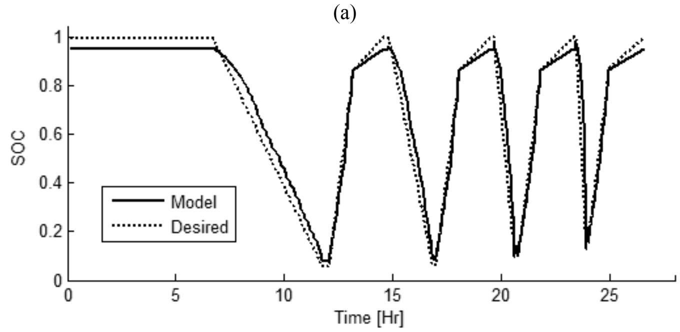


(b)

Fig. 6. ANN-based SOC prediction for training data at 0C and 75C (a) and testing data at 40C (b).



(a)



(b)

Fig. 7. ANN-based SOC prediction for training data at 0C and 40C (a) and testing data at 75C (b).

B. *Prediction in Unseen Conditions*

Secondly, the ability to generalize in previously unseen conditions of the developed SOC indicator was tested. In this experiment datasets recorded at two distinct temperatures were used as training data, while the third dataset was used as a previously unseen testing data. In this manner, the trained ANN-based model was forced to generalize and predict the SOC parameter behavior at temperature that it has not previously encountered. Clearly, a decline of performance was expected.

This decline is apparent from Table III, where the average relative training and testing errors are shown for all three possible combinations of training and testing data. While, the training error is again less than 2%, the testing error substantially increased, especially for testing at 0^0C (17.61%). The prediction and the desired response are visually compared in Fig. 6 and Fig 7. for testing at 40^0C and 75^0C.

This observation suggested that the ambient temperature has a significant influence on the characteristic behavior of the *Li/Ion* batteries. Most importantly, this means that substantially more data at different temperatures are necessary to develop a complex and accurate ANN-based SOC indicator that will perform well over the whole operational temperature range.

VI. Conclusion and Future Work

This paper presented the up-to-date results of the in-lab development of an intelligent SOCI for the *Li/CFx* battery. The designed SOCI uses artificial neural network to predict the current SOC based on the recent history of voltage, current and the ambient temperature. By accounting for the ambient temperature, the model is capable of dealing with the non-linear elements of the system behavior due to varying environmental conditions.

The reported experimental results were based on recorded data from the Battery Design Studio during several test procedures at different ambient temperatures for the *Li/Ion* battery. It was demonstrated that the developed SOCI is capable of accurate prediction with less than 2% average relative error on data at previously observed temperatures.

Future work involves developing a working model of the *Li/CFx* battery for the Battery Design Studio and applying the designed algorithm to the new data. Finally, the SOCI will be implemented into a micro-controller component constituting an evaluation embedded system.

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